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Understanding Graph-based Trust Evaluation in Online Social Networks: Methodologies and Challenges

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Online social networks (OSNs) are becoming a popular method of meeting people and keeping in touch with friends. OSNs resort to trust evaluation models and algorithms, as to improve service qualities and enhance user experiences. Much research has been done to evaluate trust and predict the trustworthiness of a target, usually from the view of a source. Graph-based approaches make up a major portion of the existing works, in which the trust value is calculated through a trusted graph (or trusted network, web of trust, multiple trust chains). In this paper, we focus on graph-based trust evaluation models in OSNs, particularly in computer science literature. We first summarize the features of OSNs and the properties of trust. Then, we comparatively review two categories of graph-simplification based and graph-analogy based approaches, and discuss their individual problems and challenges. We also analyze the common challenges of all graph-based models. To provide an integrated view of trust evaluation, we conduct a brief review of its pre-and-post processes, i.e., the preparation and the validation of trust models, including information collection, performance evaluation, and related applications. Finally, we identify some open challenges that all trust models are facing.

Categories and Subject Descriptors: A.1 [**Introductory and Survey**]; C.2.4 [**Computer-Communication Networks**]: Distributed Systems

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1. INTRODUCTION

Online social networks (OSNs) are popular tools for users, as to find new friends who share similar interests, maintain social relationships, and locate various user-generated content (UGC) [Mislove et al. 2007; Quan et al. 2011]. Nowadays, more and

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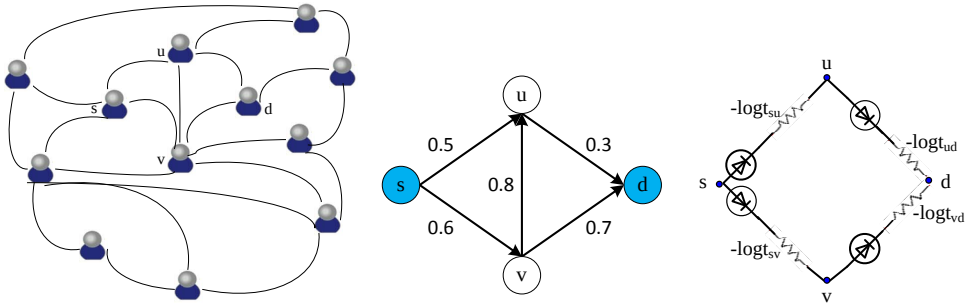


(a) A social graph (b) A trusted graph (c) Resistive network

Fig. 1. An example of (a) a social graph, (b) a trusted graph, and (c) a resistive network.

more people Join in OSNs for daily communications or even business activities. Many of those activities involve the process of forming opinions on a particular user or product, about whether to trust or not. Interactions among people through OSNs are rather complex, as they involve interactions with others, who may even be strangers. The notions of trust is the central issues in OSNs. "To be trusting is to be fooled from time to time; to be suspicious is to live in constant torment" [Wu 2009]. People face trust issues in their daily lives for decision making, which become more serious in OSNs, due to the lack of enough real life interactions and mutual understanding. Without trust, our everyday social lives, which we take for granted, would not be possible [Good 1988]. Quantifying trust in OSNs is a notoriously difficult problem, because of the complexity of OSNs and the trust itself. Studies in trust span multiple disciplines including economics [Huang 2007], sociology [Möllering 2001], political science [Newton 2001], psychology [R. 1967; Cook et al. 2005], and computer science [Marsh 1994]. Meanwhile, researches in OSNs have been conducted from multiple aspects, including network structure [Yuan et al. 2010; Watts 1999], user behaviors [Zhu et al. 2012; Bakshy et al. 2012; Crandall et al. 2008], community detection [Ciglan et al. 2013; Sathik et al. 2011; Qi et al. 2012], and so on. Furthermore, the high popularity of OSNs even leads to a new computing paradigm, that is: social computing.

The trust mechanism (or trust evaluation) is a tool used to facilitate decision making in diverse applications. Trust and trust-related issues have attracted significant attention in various networking environments, including online social networks (OSNs) [Sherchan et al. 2013], wireless communication networks [Yu et al. 2010; Jiang and Wu 2014], multi-agent systems [Pinyol and Sabater-Mir 2013], and P2P networks [Kamvar et al. 2003; Singh and Liu 2003; Marti and Garcia-Molina 2006; Kamvar et al. 2003]. As a consequence, many trust models have been proposed (and are being reviewed as in [Jøsang et al. 2007; Sherchan et al. 2013; Pinyol and Sabater-Mir 2013; Grandison and Sloman 2000]), among which, graph-based model is one of the most important branches. In this paper, we particularly focus on the current progresses and challenges of graph-based trust models in OSNs. We also give a brief introduction of the pre-and-post processes of trust models. An OSN is usually represented by a *social graph*; in which a node represents a user, and an edge represents the connection or relationship between two users. Fig. 1(a) shows an example of a social graph.

Concepts. Generally speaking, trust is "a measure of confidence that an entity or entities will behave in an expected manner [Sherchan et al. 2013]". Both the source and target can be either a party or an entity. Marsh's work [Marsh 1994] is one of the first towards formalizing trust in a computational model. However, there is no consensus on how trust should be defined. Therefore, *Trust* itself has many definitions and categories

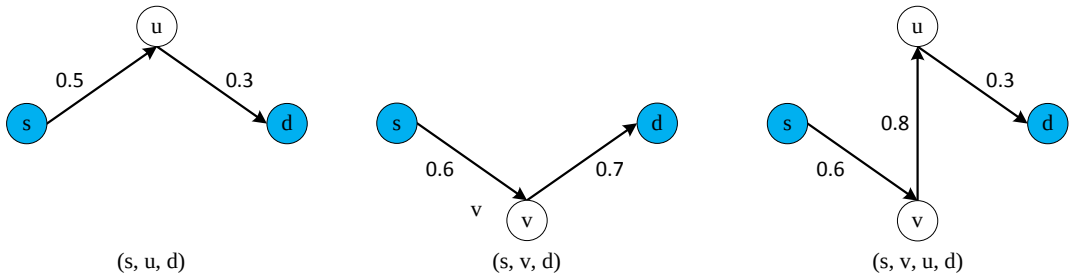


Fig. 2. The trusted paths of trusted graph in Fig. 1(b), which can be used for simplification.

[Jøsang et al. 2007; Sherchan et al. 2013]. Just mention a few examples: under the computational model, Jøsang et al. [Jøsang et al. 2007] define trust as "the subjective probability by which one user expects that another user performs a given action." In [Golbeck 2005], trust in a person is defined as "a commitment to an action, based on a belief that the future actions of that person will lead to a good outcome." Trust has also been defined as "the extent to which one party is willing to participate in a given action with a given partner, considering the risks and incentives involved [Ruohomaa and Kutvonen 2005]." Grandison et al. [Grandison and Sloman 2000] define trust as "the firm belief in the competence of an entity to act dependably, securely and reliably within a specified context." Although those definitions vary from each other, they all indicate common natures of trust (we will discuss in details later). Therefore, they are suitable to most of the existing graph-based models in OSNs.

In Fig. 1(b), u and v have known d before, and have an opinion of the trustworthiness of d; how, then, does s form her or his own opinion on d via u and v? These depend on the influence/recommendation among users and the personalities of users. A *trusted path* can be constructed through iterative recommendations, e.g., path (s, u, d) representing s's trust of d via u's recommendation. Multiple parallel and sequential paths are overlapped to form a *trusted graph* from s to d. In this paper, we call the trust models that work with a trusted graph as *graph-based models*.

Trust built through direct contact is called the first-hand trust, such as a directed link from s to u; meanwhile, that through a recommendation is called the second-hand trust, such as the trust from s to d via a trusted path (s, u, d). In Fig. 1(b), (s, u) and (u, d) are two edges of a sequential path (s, u, d); (s, u, d) and (s, v, d) are two parallel paths; (s, u, v, d) is overlapping with (s, u, d) and (s, v, d) (Fig. 2). Usually, each edge has a weight value between 0 (no trust) and 1 (full trust) to quantify each direct trust. Different models may design different ranges or even different dimensions for trust values (e.g., some model considers both trust level and confidence [Wang and Wu 2011a; Wang and Wu 2011b]). In addition, according to the role in trust evaluation, a user can be a source (or trustor, e.g., s in Fig. 1(b)), a target (or trustee, e.g., d in Fig. 1(b)), or a recommender (an intermediate user in a trusted path, e.g., u and v in Fig. 1(b)).

Categories of Trust Models. From the network perspective, trust models can be divided into two types: the local approach which considers personal bias, and the global approach which considers all users' opinions [Ziegler and Lausen 2005]. Graph-based models usually take the local approach. They can be scalar metrics, which cope with the setting where a source s is interested in a single target d; d can be another user, or a service provider. Some users have prior opinions about d. s wants to estimate the trustworthiness of d, based on the aggregated opinions of other users who he knows. In this setting, trust models analyze each user's trust opinions independently. Alter-

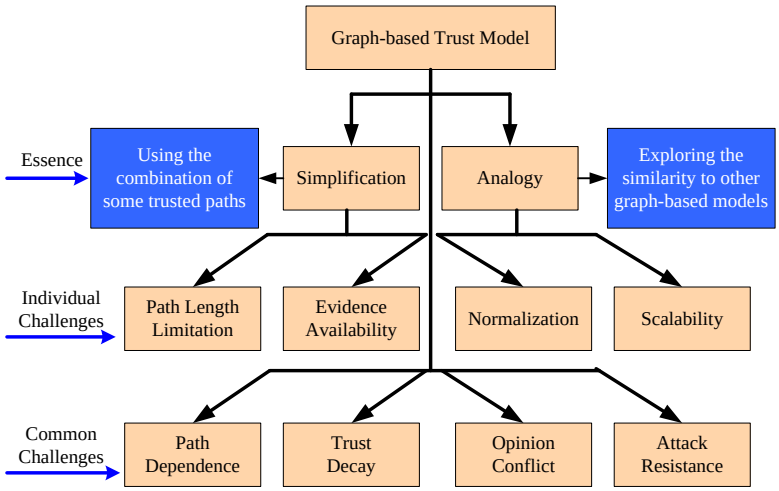


Fig. 3. The categories, essences, and challenges of graph-based trust models in OSNs: a taxonomy.

natively, in some other models, the trust of a group of nodes can be calculated at once. This type of trust model is called the *group trust metric* [Levien 2003].

Based on how to cope with the trusted graph, graph-based trust models can be classified into two categories [Wang and Wu 2011a]:

— The *graph simplification-based* approach. As its name implies, this approach simplifies a trusted graph into multiple paths, whose nodes or edges are disjoint with each other. It may also simplify a trusted graph into directed series-parallel graph [Wang and Wu 2011a], which is an important concept in graph theory. For instance, given the trusted graph in Fig. 1(b), this approach only uses one or several trusted paths in Fig. 2 for trust evaluation. The essence of this approach is to use the combination of some trusted paths, according to some pre-defined principles.
— The *graph analogy-based* approach. Different from the above approach, this approach does not remove any nodes or edges from trusted graphs. Instead of simplification, it emulates the trusted graph using other graphs. An example analogy is shown as in Fig. 1(c), which uses the resistive network to emulate a trusted graph [Taherian et al. 2008]. The essence of this approach is to explore the similarity between graph-based trust models in OSNs and other graph-based models in other networking environments, such as the network structure, the diffusion pattern, etc.

We will use this classification and compare the existing models in the following parts. Fig. 3 illustrates the overview of this survey, in which we identify the individual challenges and common challenges of graph-based trust models. To be specific, the graph-simplification based models are facing the challenges of *setting proper path length limitations* and *keeping evidence availability*. The graph-analogy based models are meeting the challenges of *normalization* and *scalability*. Moreover, all graph-based models are facing with four common challenges of *path dependence*, *trust decay*, *opinion conflict*, and *attack resistance*. Table I outlines the comparison of the mentioned representative models in details, while Table II lists how they tackle the challenges.

In this paper, we try to provide a comprehensive review on the methods and challenges of graph-based trust evaluation in OSNs. Our contributions are fourfold:

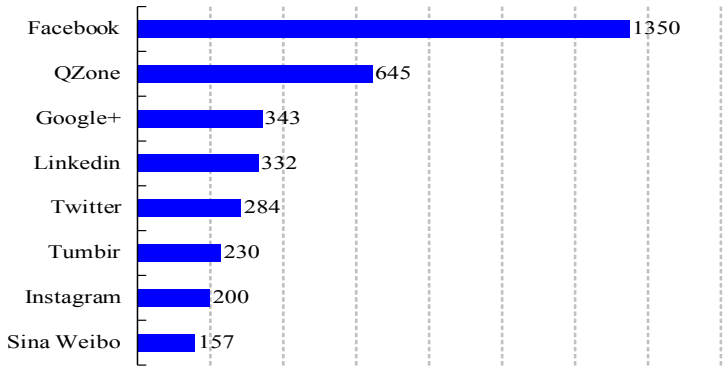


Fig. 4. Active users in leading social networks.

— We conduct a comparative study of graph-based trust models in OSNs. We survey the main techniques they use, the challenges they meet, as well as the most relevant areas. To be specific, we differentiate trust models in OSNs and classify trust evaluation techniques into two categories of graph-simplification based and graph-analogy based approaches, based on how they treat trusted graph. Then, we compare representative trust models in each category and identify their individual challenges. Finally, we point out four common challenges.
— To better understand trust models in OSNs, we analyze the features of OSNs and properties of trust in OSNs, respectively. We also analyze two other closely related concepts of trust: recommendation and influence. Besides graph-based trust models, we also provide an overview of trust models in literature, and classify them into four categories in terms of methodologies.
— We provide discussions on the pre-and-post processes of trust models, including information collection, performance evaluation, and related applications. Finally, we identify three open challenges that all trust models meet.
— We conduct empirical and theoretical analysis on representative trust models. We also discuss each model's strengths and weaknesses.

The remainder of this paper is organized as follows: Section 2 briefly summarizes the construction of OSNs and the properties and related concepts of trust. Section 3 reviews some existing works. Sections 4 and 5 survey the graph-simplification and graph-analogy based models, and discuss their challenges, respectively. Section 6 states the common challenges that all graph-based models meet. Section 7 surveys the pre-and-post processes of a trust model. Section 8 concludes this paper and proposes some open challenges that may draw more attention in the future.

2. OVERVIEW OF OSNS AND TRUST

In this section, we introduce the background of OSNs and trust in terms of its construction, related concepts and fundamental properties, as to better understand trust issues and trust evaluation in OSNs.

2.1. Construction of OSNs and Possible Trust Issues

OSNs are organized around users, and they are usually taken as a mapping from our real life to the cyber physical space. In general, OSNs have three main types of entities: users, their connections, and the information that users are generating and diffusing. Each entity has its own characteristics.

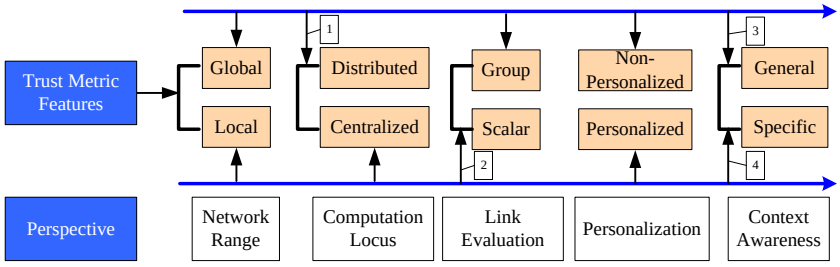


Fig. 5. The classification of trust (labels 1-4 indicate both categories are suitable).

As the first kind of entity, online users can build connections with each other and can generate their own content, which leads to the emergence of the other two kinds of entities. For the second kind of entity, similar to one's daily social life, the connections among online users are usually topic-dependent and time-sensitive. It leads to the rich variety and dynamical evolution of OSNs. Moreover, the changing speed of OSNs is much faster than that of an off-line social network. Meanwhile, the third kind of entity, i.e., the information diffused among online users via their connections, is usually large in quantity, and may cross time and space. In addition, information diffusion can be deemed as the central function of OSNs.

The above features of users, their connections, and the information they diffuse, lead to all kinds of trust issues in OSNs, such as "Can I trust the interaction partner who is a stranger to me?" "Is the information source trustful?" or "Can the service quality be guaranteed?" Those issues lead to the strong necessity of trust evaluation.

Generally, the scale of an OSN can be very large. Just to mention a few: Facebook has billions of users; over 200 million users are using Tencent QQ at the same time; Twitter has more than 100 million users. Fig. 4 (by statista report [1]) shows the statistics of active user numbers in leading social networks. Due to its large scale, the efficiency and scalability of trust models in OSNs are facing challenges. Therefore, usually a small trusted graph is used as the basis of trust models. SWTrust in [Jiang et al. 2014] is particularly proposed for trusted graph generation.

As being pointed out in [Sherchan et al. 2013], network structures can affect the evidence for trust and the resulting trust degree. From the network structure's view, OSNs have been studied to bear the characteristics of small-world networks [Watts 1999; Yuan et al. 2010]: higher clustering and shorter distances between any two nodes. Based on this, searching proper trust evidence in large OSNs can be completed.

2.2. Concepts and Categories of Trust

We have mentioned some key concepts in the introduction section. Here, we provide more formal definitions to better describe trust and trust evaluation.

First of all, we provide the definition of trust we use in this survey. As we have mentioned before, several definitions of trust have been presented and they are suitable to graph-based trust models in OSNs. Hence, we do not present any new definition, rather use the one from Jøsang in [Jøsang et al. 2007].

Definition 2.1. *Trust*. "Trust is the subjective probability by which one user expects that another user performs a given action [Jøsang et al. 2007]."

[1] http://www.statista.com/statistics/272014/global-social-networks-ranked-by-number-of-users

Next, we describe formal definitions of *trustor*, *trustee*, *recommender*, *trusted path*, and *trusted graph*, which are commonly-used concepts in graph-based trust models.

Definition 2.2. *Trustor*. A user who is trying to know the trustworthiness/trust degree of another user, is taken as the trustor.

Definition 2.3. *Trustee*. A user whose trustworthiness/trust degree is being evaluated, is taken as the trustee.

Definition 2.4. *Recommender*. An intermediate user who helps the trustor to evaluate the trustworthiness/trust degree of the trustee, is taken as the recommender.

Definition 2.5. *Trusted Path*. A path that consists of a trustor (the source), several recommenders, a trustee (the target), and trust relations among them, is taken as a trusted path from the trustor to the trustee.

Definition 2.6. *Trusted Graph*. All the trusted paths starting from a trustor and ending with a trustee, form a trusted graph from the trustor to the trustee.

We differentiate the trusts being used in a trusted path into two types, as in [Jøsang et al. 2006b]:

Definition 2.7. *Referral Trust*. Trust in the ability (of a recommender) to **recommend** a good service provider (i.e., trustee), represents referral trust.

Definition 2.8. *Functional Trust*. Trust in actually being a good service provider (i.e., trustee), represents functional trust.

From the above two definitions, we can see that referral trust is usually originated from a source (i.e., trustor) to a recommender, or from a recommender to another recommender; meanwhile, functional trust is usually started from a directly connected neighbor to the target (i.e., trustee).

Based on some prior work including [Guha 2003], [Levien 2003], [Ziegler and Lausen 2005], and [Jøsang et al. 2007], we provide a classification of trust metric features as shown in Fig. 5. It considers multiple aspects including network range (global or local), computation locus (distributed or centralized), link evaluation (group or scalar), personalization (personalized or not), and context awareness (general or specific). Next, we provide several new concepts based on above classification.

Definition 2.9. *Global Trust*. Metrics for measuring a global trust consider the opinions of all users and all trust relations among them, i.e., it is calculated based on complete trust information in the network.

Definition 2.10. *Local Trust*. Metrics for measuring a local trust consider the opinions of partial users, usually from neighborhood of the trustor.

Definition 2.11. *Group Trust Metric*. Group trust metrics calculate the trustworthiness of a group of users simultaneously.

Definition 2.12. *Scalar Trust Metric*. Scalar trust metrics calculate the trustworthiness of each user independently.

Definition 2.13. *Personal Trust*. The trustworthiness of a user from the view of a particular user (e.g., the trustor), is taken as personal trust.

Definition 2.14. *Specific Trust*. The trustworthiness of a user on some specific topic or topics, is taken as specific trust.

Definition 2.15. *General Trust*. The trustworthiness of a user without specifying any topic or topics, is taken as general trust.

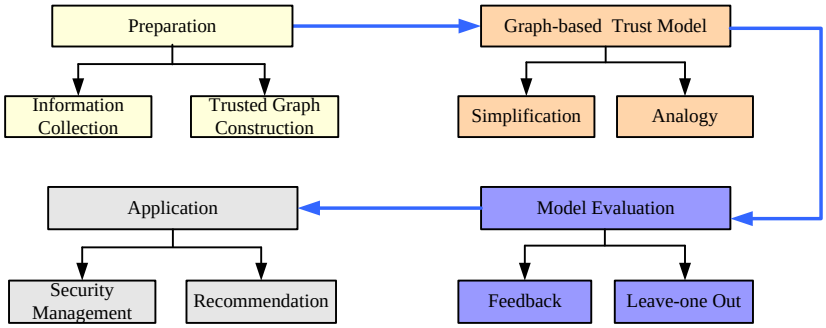


Fig. 6. The integrated process of trust evaluation in OSNs.

In Fig. 5, the arrows connecting multiple features represent their correlations. To be specific, for global trust, the computation can be done either in a distributed or centralized way; it evaluates groups of trust assertions at once; it is usually non-personalized; it can be either general or with some specific topics. Meanwhile, local trust is usually calculated in a centralized way; it evaluates each trust assertion independently; it is usually personalized; it can be either general or with some specific topics.

Generally speaking, a global trust is used to represent the overall reputation, while a local trust indicates personal opinion. Although they use different network range for trust evaluation, both global and local trust can be predicted using graphs. Fig. 6 shows the integrated process of graph-based trust evaluation in OSNs (in fact, it also applies in other networking environments). There are four basic steps: (1) Collecting information for trust, i.e., evidence collection for evaluating a user's trust degree; (2) Constructing trusted graph, i.e., managing trust evidence using a graph; (3) Conducting trust evaluation, i.e., designing algorithms to calculate trust degree; (4) Applying the results to other applications (e.g., security management, recommendation system).

As to this survey, the main scenario we are considering is "a source s wants to know the trustworthiness of a target d." For this end, a trust model is trying to collect trust evidence and calculate the trust degree of d, from the view of s. The small-world characteristic of OSNs make it possible to collect evidence for trust evaluation. Most of the representative models we review in this survey fall into the range of scalar/local/personal-trust models, including TidaTrust [Golbeck 2005], MoleTrust [Massa et al. 2005], MeTrust [Wang and Wu 2011a], SWTrust [Jiang et al. 2014], RNTrust [Taherian et al. 2008], FlowTrust [Wang and Wu 2011a], and GFTrust [Jiang et al. 2015b]. A few of them are group-trust models, including Appleseed [Ziegler and Lausen 2005] and Advogato [Levien and Aiken 1998].

2.3. The "START" (Properties) of Trust in OSNs

Trust in OSNs has several common properties [Jøsang et al. 2007; Sherchan et al. 2013]. Here, we briefly introduce five typical and fundamental ones, which we call the "**START**" of trust: **s**ubjective, **t**opic-dependent, **a**symmetric, **r**isking betrayal, and **t**ime-sensitive. Note that, the mentioned properties in this subsection are extracted from the trust itself. In the next subsection, we will describe some typical properties of trust from the computation's view.

Trust is subjective, since "trust on a person" is a kind of opinion from a specific user. In fact, the notion of trust has been widely studied in the fields of psychology and sociology [Marsh 1994]. This property indicates that trust is generally personalized, i.e., different people may have different trust opinions towards the same person. The

subjective and personalized nature further leads to the difficulty of measuring it. In particular, how can we collect evidence to estimate people's trust in others, given that people usually do not express their trust opinions frankly, due to some concern like worsening a relation with someone. It is even more challenging to consider how we can integrate uncomplete and inaccurate evidence to make an accurate prediction.

Trust is topic-dependent, because our humans have different expertise in different fields. For instance, an expert A in computer science may not be good at music. Therefore, we may trust A when considering problems in computer science, while not in those of music. The topic-dependence property is consistent with that of social connections, since trust can be deemed as a special connection.

Trust is asymmetric, which indicates that the degree to which A trusts B is usually not equal to that of B trusting A. To some degree, we can even say that the asymmetric property of trust is caused by its subjectivity.

Trust is risking betrayal, indicating that when we want to place trust on someone, usually there is risk (some probability) that things may not happen as we have expected. And if that happens, it may lead to some cost or loss to us; and we may never trust that person again. Therefore, trust is "hard to gain, easy to lose." According to the interaction experience, people will refine their initial trust opinions on the target and even those on the recommenders. This is exactly how trust evolves.

Similar to the topic-dependence property, trust is time-sensitive, because trust is a type of human relations. As time passes on, some old relations may weaken, while some new relations can be built. In addition, people's opinions may vary with time, which also leads to the change of trust.

2.4. The Properties of Computation Trust in OSNs

We describe five typical properties of trust in the above subsection, which can be taken as the nature or the feature of trust. In this subsection, we will introduce two typical properties of computation trust in OSNs: *propagative* and *composable*, which can be deemed as the basis or the foundation of trust evaluation.

The propagative property of trust indicates that trust relations can be diffused along a chain. For example, s trusts u, and u trusts d; but s does not know d. However, s can derive some trust on d, based on the degree s trusts u and u trusts d. This property is exactly the reason why trust models can search iterative recommendation chains for trust evaluation. However, this property does not mean "the strict transitive relation" in mathematics, in which s trusts u and u trusts d will lead to the conclusion that s trusts d. Therefore, some work indicates the propagative property of trust as "weak-transitive" (e.g., [Golbeck 2005],[Jøsang et al. 2006a]), while some others identify the "non-transitive" as one property of trust (e.g., [Sherchan et al. 2013]).

The composable property of trust indicates that, the trust values induced from multiple trusted paths can be integrated as one value. From some degree, the composable property is a special kind of propagative property. For instance, Sun et al. [Sun et al. 2006a] uses concatenation propagation and multi-path propagation to differentiate them. Composing several trusted paths is quite difficult, especially when different paths providing contradictory information [Sherchan et al. 2013]. Using the composability property, Richardson et al. [Richardson et al. 2003] propose a composition function, as to combine trust evidence. Jøsang et al. [Jøsang et al. 2006b; Jøsang 1999; Jøsang et al. 2006a] integrate trust values using subjective logic. More recently, Liu et al. [Liu et al. 2014] propose a trust model using three-valued subjective logic.

2.5. Closely Related Concepts

Before introducing graph-based trust models, we would like to analyze two concepts that are closely related with trust: (social) influence and recommendation. They can

help us understand how interactions happen and how trust propagates. [Yedidia et al. 2001] provides a strict analysis of the generalized belief propagation. Note that, reputation, which is often taken as the average of global trust, is another closely related concept. Here, we do not introduce it, since there are many other works on it (e.g., [Houser and Wooders 2006; Sabater and Sierra 2002; Jøsang et al. 2007; Srinivasan et al. 2008; Mármol and Pérez 2010; Noorian and Ulieru 2010]).

As we know, trust is the basis of almost all online interactions. Without trust, people cannot cooperate well with others, and the online system cannot run regularly.

Social influence can be taken as the tool that makes user interactions happen. Rashotte [Rashotte 2007] defines it as "a change in an individual's thoughts, feelings, attitudes, or behaviors that result from interactions with another individual or a group." Suppose s wants to know the trustworthiness of d, and s asks u for advice. If u suggests that s does that, and s decides to do it, we can say that s is influenced by u. [Jiang et al. 2014] studies the construction of a user's social influence from two aspects of the user, himself, and his connections with friends, which can help lead to a better understanding of social influence.

Recommendation is the method allowing opinions to propagate. During the process of trust evaluation from s to d in Fig. 1(b), the trust from s to u and from s to v can be taken as referral trust [Jøsang et al. 2006a], which is the trust with respect to the ability to recommend a good target. u and v can be taken as recommenders. The final trust in which s puts on d, through the referrals of u and v, is called recommendation trust [Wang and Wu 2011a], which is the trust derived from others' experiences.

In summary, we can say that, trust, influence, and recommendation are three key driving powers that make an online social network run forward. This is also suitable for the real world social network.

3. RELATED WORK

We first review some existing surveys on trust and trust models. Then, we review works on trust evaluation in four categories in terms of their methodologies. Finally, we discuss some related works in the system and application communities.

3.1. Existing Surveys on Trust

Due to its importance in multiple aspects, trust has been widely studied and reviewed. Jøsang et al. [Jøsang et al. 2007] propose a widely-cited survey on the notions, categories and applications of trust and reputation systems, particularly for online service provisions. Sherchan et al. [Sherchan et al. 2013] present an important review of trust in social networks, in which they comprehensively examine trust definitions and measurements, from multiple fields including sociology, psychology, and computer science. Noor et al. [Noor et al. 2013] present an survey of trust models in cloud environments. Most recently, Cho et al. [Cho et al. 2015] propose a comprehensive survey, aiming to outline the foundations of trust models. Yu et al. [Yu et al. 2012] study the effects of trust scheme in wireless sensor networks, mainly in terms of attack resistance; in which they categorize attack types and countermeasures. Cho et al. [Cho et al. 2011] conduct a survey on trust schemes in mobile ad hoc networks (MANETs), in which they discuss multiple aspects, including the classifications and potential attacks. Marmol et al. [Marmol and Perez 2010] try to summarize common properties of trust/reputation models in distributed systems. Ruohomaa and Kutvonen [Ruohomaa and Kutvonen 2005] provide an overview of the literature. They also list some example metrics, in two phases of modelling trust and building a specific solution. Grandison and Sloman [Grandison and Sloman 2000] examine different trust definitions, and provide one for trust in Internet applications.

There are more works on reputation, a concept that is closely related with trust. [Jøsang et al. 2007], [Marti and Garcia-Molina 2006], [Sabater and Sierra 2005], [Noorian and Ulieru 2010], and [Yao et al. 2012a] provide the comprehensive review in the reputation system (or the hybrid system of trust and reputation). For instance, [Hoffman et al. 2009] focuses on the characterization of reputation systems, particularly from the perspective of computer science.

3.2. Trust Models in Methodologies

From the view of sociology, the trust relationship is one of the most complex social relation. A reason for this lies in its dynamic properties as we have mentioned in Section 2. Another reason is that, a trust relation involves multiple factors of assumptions, expectations, behaviors, and environments. Therefore, it is very challenging to measure and predict trust. As a new method in the field of network and information security, trust evaluation has been studied in P2P networks, mobile ad hoc networks, multi agent systems, and semantic web. The core of trust evaluation is the expression and measurement of trust relations, and the construction of a trust evaluation scheme. Currently, researches on trust evaluation are conducted using the tools in mathematics, statistics, or artificial intelligence. To be specific, many trust models are proposed based on fuzzy theory, subjective logic, machine learning, information entropy, game theory, graph theory, and so on. For instance, among existing path-based propagation methods, there are the Dempster-Shafer combination rule [Jøsang and Pope 2012; Shafer 1976] from statistics, serial-parallel merge [Jøsang et al. 2006b] using subjective logic, triangular norms [Wang and Wu 2011a] as logical conjunctions from classic logic, and path concatenation [Richardson et al. 2003] from path algebra. In the following parts, we review existing work briefly in four categories in terms of the methodology:

— **D-S evidence theory and subjective logic based approaches**. To deal with the subjectivity property of trust, this approach introduces the process of inferring uncertainty. The Dempster-Shafer theory (D-S Theory) [Dempster 1967; Shafer 1976] is exactly a general framework for reasoning with uncertainty. It can combine evidence from different sources, and get a final degree of belief (using the belief function). Jøsang et al. [Jøsang et al. 2006b; Jøsang et al. 2008] improve the D-S evidence theory, and propose a trust model with subjective logic (TNA-SL). As being pointed by the authors, in this model, "the confidence of a trust value is equivalent to the certainty of the corresponding opinion." Liu et al. [Liu et al. 2014] propose to use three-valued subjective logic for trust evaluation. They differentiate the posteriori and the priori uncertainty spaces, so as to better describe and manage trust evidence. The former is introduced to store the evidence distorted from certain spaces as trust is propagated, and the latter is used to control the evidence size as trusts are combined.

— **Approaches using traditional mathematics tools (probability statistics, fuzzy logic, etc.)** . This approach tries to "provide a sound mathematical model for trust evaluation [Sherchan et al. 2013]." Probability models represent trust values as a probability, and evaluate trust using probability functions (e.g., [Sun et al. 2006b]). Taking the similar idea with PageRank [Page et al. 1999], each node in EigenTrust [Kamvar et al. 2003] is assigned with a global trust value. Kuter and Golbeck [Kuter and Golbeck 2007] propose an algorithm, SUNNY, to estimate trust by probabilistic confidence models. Commonly used probability tools in trust evaluation include the Beta model [Li and Wu 2010], the Bayesian model [Nielsen et al. 2007], and the hidden markov model (HMM) [ElSalamouny et al. 2010] [ElSalamouny et al. 2009]. Some trust models use Bayesian inference [Lee 2012], where the probability can be updated or inferred with observations. Pearl [Pearl 1999] presents a more general belief propagation algorithm for Bayesian networks to solve inference problems.

A comprehensive survey of inference problems has been reported in [Yedidia et al. 2002], which involves many fields, such as statistical physics, computer vision, and artificial intelligence (AI). Another commonly-used tool is fuzzy logic. It provides reasoning rules to deal with fuzzy metrics. Trust itself is fuzzy in some degree, due to the involved uncertainties. Fuzzy logic is able to handle uncertainty and imprecision effectively, and is therefore seems ideally suited to reasoning about trust. REGRET in [Sabater and Sierra 2002] and k-FuzzyTrust in [Chen et al. 2014] fall in this category. In addition, Xia et al. [Xia et al. 2011] build a subjective trust management model AFStrust, which considers multiple factors including direct trust, recommendation trust, incentive function and active degree, and treats those factors based on the analytic hierarchy process (AHP) theory and the fuzzy logic rules. Lin et al. [Lin et al. 2009b] propose a method of hierarchical fuzzy trust evaluation for P2P network. However, fuzzy logic systems meet two main issues: one is how to design proper reasoning rules, the other is how to reduce the number of involved rules and decrease their computation requirements.

— **AI and information theory based approaches**. Works in this category usually model the trust evaluation task into a learning problem or a decision support system. They seek to apply machine learning methods to overcome the generalizability issues in Bayesian trust models. [Liu et al. 2014] describes how to build robust reputation systems using machine learning techniques, and defines a framework for translating a trust modeling problem into a learning problem. [Peng et al. 2010] tries to improve the security routing in MANETs by employing a dynamic trust mechanism, which considers multiple constraints and applies the idea of collaborative filtering. [Huynh 2009] provides a mechanism to capture the trust evaluation process of users, which can be replicated by computers. A user can specify two things: (1) Given the information about the target, how he selects a trust model; and (2) how he configures the model. Liu et al. [Liu et al. 2013a] propose a machine learning based trust framework, especially for large-scale open systems. However, the above mentioned approaches are often model-centric. That is, they put more focus on the model itself, rather than on the data. They also overlook the importance of system adaptability, which is essential for service selection [Hauke et al. 2013]. This will lead to the risk of unrealistic model assumptions. [Hauke et al. 2013] points out several requirements for probabilistic trust models, as to improve their robustness using supervised learning. They also explore a real-world data set, as to validate the effectiveness of supervised methods.

— **Graph-based approaches**. The main focus of this paper is on this category, i.e., the graph-based trust models. Following the category in [Wang and Wu 2011a], we broadly classify them into two categories: simplification or analogy based. Sun et al. [Sun et al. 2006b] give an theoretic framework on trust propagation, by stating two axioms as possible guiding principals: “concatenation propagation of trust does not increase trust,” and “multi-path propagation of trust does not reduce trust.” [Jøsang et al. 2006b; Jøsang et al. 2008; Zuo et al. 2009] propose the methods of simplification. The basic idea is to reduce the trusted graph into serial/parallel trusted paths or node/edge disjoint multiple paths [Golbeck and Hendler 2006; Mui et al. 2002; Sun et al. 2006b]. More works using simplification approach include TidalTrust [Golbeck 2005], MoleTrust [Massa et al. 2005], MeTrust [Wang and Wu 2011b], SWTrust [Jiang et al. 2014], etc. TidalTrust, MoleTrust and SWTrut are based on breadth-first search. TidalTrust selects the strongest shortest path, while MoleTrust uses the hop count to control the length of the selected paths, and SWTrust limits the width of each hop. These approaches, however, may suffer from the information-loss problem. Some more interesting approaches are graph analogy-based. In [Mahoney et al. 2005], a generalized reliability theory is applied to a trusted network with failure-

prone elements. In RNTrust [Taherian et al. 2008], a trusted graph is being transformed into a resistive network. Mislove et al. [Mislove et al. 2008] propose the Ostra scheme, to bound the total amount of unwanted communication a user can produce. The intuition is that it is difficult for a user to create an arbitrarily large number of trust relationships. Tran et al. [Tran et al. 2009] further propose SumUp, to detect sybils using the technique of adaptive vote flow aggregation. The work of Wang and Wu, FlowTrust in [Wang and Wu 2011a], relates the amount of flow to trust, considers both the trust and confidence, and converts the trust propagation to a maximum flow, minimum cost problem. [Jiang et al. 2015b] addresses trust evaluation using a more general network flow model with leak, representing a trust decay.

3.3. Researches on Recommendation and Influence

As we have mentioned before, recommendation and influence are two closely related concepts of trust. In fact, the two concepts are also hot topics in both academic research and practical systems. Researches on recommendation try to predict a user's opinion on a specific item, as to recommend proper item to the user. *Collaborative filtering* [Terveen and Hill 2001] is a non-trust-based technique used by some recommendation systems, which predicts a user's interests by considering many others' preferences in a community. Some efforts have been made to combine trust-based and collaborative filtering approaches [Hang et al. 2013; Resnick et al. 2000; Jiang et al. 2014].

In recommendation systems, a user's opinion (called rating) is usually represented as a numeric value. Anderson et al. [Andersen et al. 2008] uses a finite set, $\{+, -, 0\}$, to represent positive, negative, and neutral ratings, respectively. In our previous work in [Jiang et al. 2014], an opinion is measured by fluid temperature, which can easily be updated based on the volume and temperature of the new fluid.

In addition, people can be associated with both an "innate opinion" and an "expressed opinion" [Goel et al. 2010] for an item. The former is formed by the user himself, and is independent with his social interactions; while the latter can be shaped and influenced by others [Das et al. 2013]. In our work [Jiang et al. 2014], these two types of opinions can be treated with the initial and mixed fluid. The work in [Zhu et al. 2012] finds that, a person's opinion can be significantly impacted by others' opinions. Bakshy et al. [Bakshy et al. 2012] conduct several experiments, and the results validate that stronger ties are more influential, and weak ties are more effective for novel information propagation. Wang et al. [Wang et al. 2014] propose a model to evaluate social influence. It provides a fine-grained framework in which users can define some specific features. The maximization of influence has been modeled as an optimization problem [Kempe et al. 2003] with various extensions [Chen et al. 2009; Chen et al. 2010; Chen et al. 2011; Maghami and Sukthankar 2013; Zhang et al. 2013].

3.4. Trust-related Systems and Applications

Trust-related systems and applications can be generally classified into two categories: experimental or commercial. Among experimental systems, FilmTrust [Golbeck 2005] uses TidalTrust to rate films. In some sites, such as Advogato [Levien and Aiken 1998], users can rank others based on their skills on software development. To guard against spam, each user is assigned a trust quota (flow), which can be redistributed to other users, subject to the trust capacity constraint at each user. The objective is to distribute quota to as many trustful users as possible (and to cut off malicious users), through the way of a modified max flow. Appleseed [Ziegler and Lausen 2005] provides a couple of quota distribution rules to neighbors. Among commercial systems, eBay [Resnick et al. 2000; Resnick and Zeckhauser 2002] uses voting networks by votes of $+$, $-$, or 0. Amazon [Ama 2014] adopts a rating from 1 to 5. Multiple-level ratings have been widely used in other fields, e.g., restaurant ratings in Zagat [Zag 2014] and Yelp [Yel

2014]. Epinions [Massa and Bhattacharjee 2004] website provides reviews of products by real people. In Epinions, users can add other users into their webs of trust, if they found their reviews are helpful. This approach can relieve the sparsity problem that has hampered the collaborative filtering approach. Rating aggregations are usually governed by a set of axioms [Altman and Tennenholtz 2005; Andersen et al. 2008].

In large-scale distributed systems (e.g., peer-to-peer systems), a malicious user may pretend to have multiple identities, as to make profits or mislead other users; we call these *sybil attacks*. Leveraging the observation that sybil nodes tend to be poorly connected to non-sybil nodes [Viswanath et al. 2011], a series of works have been proposed to detect sybils, including SybilGuard [Yu et al. 2006], SybilLimit [Yu et al. 2008], SybilInfer [Danezis and Mittal 2009]. Yu et al. propose SybilGuard [Yu et al. 2006] and SybilLimit [Yu et al. 2008]. Both of them enable an honest node s (the verifier) to decide whether or not to accept another node d (the suspect). In this sense, it is very similar to a trust model, which tries to help s decide the trustworthiness of d. All three schemes employ random walk approaches. Their algorithmic differences are present in that [Danezis and Mittal 2009; Viswanath et al. 2011] SybilGuard uses a single instance of a very long random route, SybilLimit employs multiple instances of short random walks to sample nodes from the honest set, and SybilInfer takes Bayesian inference on the results of the random walks. Viswanath et al. [Viswanath et al. 2011] provide a deep analysis and comparison of those schemes, which proves that they are all detecting local communities, and suggests that they can be taken as "implicitly ordering or *ranking* nodes in the network."

Some follow-up work includes SumUp [Tran et al. 2009] and Iolaus [Molavi Kakhki et al. 2013]. SumUp [Tran et al. 2009] detects sybils with the technique of adaptive vote flow aggregation, which creates a voting envelope with appropriate link capacities around the collector. Iolaus [Molavi Kakhki et al. 2013] leverages the underlying social network of online content rating systems as a defense against sybil attacks and the "buying" of ratings from users. The former attack is handled by weighing ratings, and the latter is being treated by relative ratings to mitigate the effect of "bought" ratings.

Website ranking is similar to a global trust and reputation management system. Ranking is usually distributed link-based. PageRank [Page et al. 1999] used in Google and RankDex [Li 1998] used in Baidu, maintain one ranking number for each site (similar to a trust degree for each user). Ranking numbers are iteratively calculated through number exchanges with neighbors. HITS [Kleinberg 1999] in Ask.com maintains two ranking numbers for each site: hubs and authorities, which again are calculated iteratively through neighbor exchanges. CLEVER [Clever 2014] in IBM uses the notion of community in ranking decisions. TrustRank [Gyöngyi et al. 2004] relies on initial trusted seeds to carefully rank other sites to mitigate spam.

4. GRAPH SIMPLIFICATION-BASED APPROACH

We review some of the major works using the graph simplification-based approach, including TidaTrust [Golbeck 2005], MoleTrust [Massa et al. 2005], MeTrust [Wang and Wu 2011a], and SWTrust [Jiang et al. 2014]. We first describe their basic ideas with examples. Next, we discuss the challenges they meet. Finally, we present the main findings of empirical studies, and we analyze their time complexity and scalability.

4.1. Representative Models

— **TidalTrust**. Golbeck [Golbeck 2005] proposes TidalTrust. Given two people in the network, TidalTrust generates a recommendation about the trust degree that one person can put on the other, based on the trusted paths. The trusted paths are explored by taking breadth-first search from the trustor to the trustee. Note that only the shortest strongest trusted paths are used in TidalTrust, for which the pros and

cons will be discussed later. The calculation of trust from s to d is done as follows:

$$t_{sd} = \frac{\sum_{j \in Ns,\ t_{sj} \geq max} t_{sj} t_{jd}}{\sum_{j \in N_s,\ t_{sj} \geq max} t_{sj}}, \tag{1}$$

where N_s is the neighbor set of s, and max is the threshold of being trustful (i.e., j is taken as trustful only if $t_{sj} \geq max$). In fact, the name "TidalTrust" was chosen because the similarity between the calculation method and a tidal stream: calculations sweep forward from the trustor to the trustee, and then pull back from the trustee to return the final value to the trustor. Taking Fig. 1(b) for instance, TidalTrust will take the trusted path (s, v, d); and it will gain a result of $t_{sd} = 0.7$.

— **MoleTrust**. Massa et al. [Massa et al. 2005] propose MoleTrust, which has two steps. The first step is to delete cycles, by sorting users based on their shortest distances from the trustor s. Then, it considers all users up to a maximum-depth, which is given as an input. It is worth noting that the maximum depth is independent of any specific user. Therefore, the trusted graph they use is actually a reduced *directed acyclic graph* (DAG). MoleTrust first calculates the trust degrees of users who are one step away from s, then two steps, three steps, and so on. In addition, the trust degree of a user who is k steps away from the source, only depends on those of users who are k-1 steps away. In this way, each user's information is used only once. The calculation is done with the weighted average of all the trustful incoming neighbors' trust towards the trustee d, using Eq. 2, as follows:

$$t_d = \frac{\sum_{i \in N_d^+} t_i t_{id}}{\sum_{i \in N_d^+} t_i}, \tag{2}$$

where N_d^+ is the trustful incoming neighbors of d, and t_i is the trust degree of i. Taking Fig. 1(b) for instance, we have $t_u = 0.5$, $t_v = 0.6$, and $t_d = \frac{0.5*0.3+0.6*0.7}{0.5+0.6} \approx 0.52$.

— **MeTrust**. Wang and Wu [Wang and Wu 2011a] propose a trust evaluation system, MeTrust, using multi-trusted paths with multi-dimensional evidence. They conduct trust computation at three layers. The node layer considers multi-dimensional trust; each user can assign a different weight for each dimension. The path layer applies the Frank t-norm, as to control the rate of trust decay during combination. The graph layer consists of three algorithms: GraphReduce, GraphAdjust, and WeightedAverage, to simplify trusted graphs. Since MeTrust considers many possible scenarios and variable settings can be flexibly selected, we prefer to take MeTrust as a comprehensive framework rather than a specific model or algorithm.

— **SWTrust**. In graph-based trust models, it is usually assumed that a small trusted graph already exists. Our previous work in [Jiang and Wang 2011; Jiang et al. 2014] proposes a framework, SWTrust, to preprocess an OSN and generate a trusted graph. SWTrust takes the basis of the small-world network characteristics of OSNs and the theory of "weak ties [Granovetter 1983]." It uses the information of users' active domains to construct the trust value, which is more objective compared to explicit trust ratings. Neighbors of a user are divided into three categories of local neighbors, longer ties, and longest ties, according to their social distance from the user. Then, it takes width adjustable breadth-first search to discover trusted paths, where we uniformly select next-hop neighbors from three categories in each search step. This work is the first that "focuses on generating small trusted graphs for large OSNs, and explores the stable and objective information (such as users' domain) for inferring trust [Jiang and Wang 2011; Jiang et al. 2014]". Besides generating trusted graphs, SWTrust also implements eight trust prediction strategies, by combine three

Table I. Comparison of existing graph-based trust models in OSNs.

Model*	Cat.	Computation Model	Trust Value	Dimension	Trust Information	Test data set
TidalTrust	S	linear model	discrete, [1, 10]	1	trust	FilmTrust
MoleTrust	S	linear model	continuous, [1, 5]	1	trust	Epinions
MeTrust	S	linear model	continuous, [0, 1]	2	confidence, trust	-
SWTrust	S	linear model	continuous, [0, 1]	1	trust	Epinions
RATE	S	linear model	continuous, [0, 1]	4	trust, influence, uncertainty, cost	Epinions
MFPB-HOSTP	S	linear model	continuous, [0, 1]	3	trust, intimacy, role impact	Enron email*
RN-Trust	A	resitive network	continuous, [0, 1]	1	trust	-
Appleseed	A	spreading activation	continuous, [0,in(s)]	1	trust	-
Advogato	A	network flow	discrete, 4 levels	1	trust	Advogato
FlowTrust	A	network flow	continuous, [0, 1]	2	confidence, trust	-
GFTrust	A	network flow	continuous, [0, 1]	1	trust	Epinions; Advogato

1. 2nd column, "Cat." is short for category; 'S'/'A' is short for simplification/analogy.
2. Source of models: TidalTrust [Golbeck 2005]; MoleTrust [Massa et al. 2005]; MeTrust [Wang and Wu 2011a]; SWTrust [Jiang et al. 2014]; RN-Trust [Taherian et al. 2008]; Appleseed [Ziegler and Lausen 2005]; Advogato [Levien and Aiken 1998]; FlowTrust [Wang and Wu 2011a]; GFTrust [Jiang et al. 2015b].
3. Enron email [Goldstein et al. 2006].

factors of propagation functions (*Min* and *Multiply*), aggregation functions (Max and *Weighted Average*), and whether only taking shortest paths or not.

In addition, our previous work, [Jiang et al. 2013; Jiang et al. 2015a], proposes the RATE algorithm, as to select proper recommenders to infer trust. In that work, we study how to measure the quality of recommenders, and how to select proper amount of recommenders. Liu et al. [Liu et al. 2013b] proposes MFPB-HOSTP, a "Multiple Foreseen Path-Based Heuristic algorithm," as to find trust paths.

4.2. Challenge: Path Length Limitation & Evidence Availability

Graph-simplification based approaches use both the propagative and composable properties of computation trust. For a trusted path, propagation works in this way: if s trusts u, and u trusts v, then s can derive some trust towards v. Then, it faces the challenge of setting a proper limitation of path length; a smaller limitation may lead to fewer paths, while a larger one may cause inaccurate prediction. For multiple trusted paths in a trusted graph, how to combine the available evidence is the main challenge.

For this point, Golbeck [Golbeck 2005] conducts some experiments and finds that a shorter path can predict trust with a higher accuracy. Hence, in the proposed TidalTrust algorithm, she only uses the "shortest and strongest" paths for trust inference. The approach has its two sides. On one side, it can filter out most of the noisy evidences; on the other side, some useful information may be neglected. Jøsang et al. [Jøsang et al. 2006a] point out that "trust can be diluted through the propagation process," in which a longer trust referral chain leads a weaker predicted trust. Lesani and Montazeri [Lesani and Montazeri 2009] present a different view. They suggest that the information inferred from a highly trustful long chain, may be much more precise

than that from a low trustful short chain. Their work indicates the balance of "trust availability" and "path reliability." Cho et al. [Cho et al. 2012] make a further step and try to identify the optimal path length and generate the most accurate trust, basing on "a tradeoff between trust availability and path reliability over trusted space." Kim et al. [Kim and Song 2011] study those problem comprehensively. They compare four trust prediction strategies: "weighted mean aggregation among shortest paths," "min-max aggregation among shortest paths," "weighted mean aggregation among all paths," and "min-max aggregation among all paths." Among those four, the "weighted mean aggregation among all paths" performs the best. This finding indicates that more trust evidence may help for trust prediction.

However, to the best of our knowledge, there is still no conclusion about *the best trusted path length*, and *the most proper number of paths*, even in a specific context. The challenge is still open and worth further attention. Nevertheless, the problem is context-dependent, and the key is to find a balance between path length [Kim and Song 2011] and evidence availability [Cho et al. 2012].

4.3. Empirical Studies and Analysis

We have conducted comparative experiments in [Jiang and Wang 2011; Jiang et al. 2014], with respect to TidalTrust, MoleTrust, and SWTrust. Here, we only report the main findings as follows:

— SWTrust is more robust to vicious nodes for using stable and objective information to infer trust. It can weaken the effect of vicious nodes because the information cannot be changed at will.
— In most cases, MoleTrust and SWTrust are more accurate than TidalTrust. This is because there is usually a single shortest strongest path that TidalTrust uses, and the opinion from multiple paths is usually better than that of a single path, as to avoid being subjective and one-sided.
— SWTrust is more comprehensive for considering *trust conflict*, in dealing with controversial users. Introducing the factor of *trust conflict* can increase accuracy because it can weaken the negative effect of one-sidedness, especially when using the Max function to do aggregation.

Time complexity and scalability. The main operation in TidalTrust, MoleTrust, and SWTrust is breadth-first search, for which the complexity is $O(|V|+|E|)$, where $|V|$ is the number of nodes and $|E|$ is the number of edges. Moreover, all three methods take some strategy to reduce complexity. TidalTrust takes only the shortest and strongest paths. MoleTrust limits the hops from source, e.g., MoleTrust1 only considers the direct neighbors of the source, MoleTrust2 only considers the neighbors of the source's neighbors (2-hop distance from source), and so on. SWTrust restricts the width in each hop, with a parameter (say, $w = 3, 6, 9...$) representing how many neighbors will be selected. As to the scalability, since only small subsets of relatively constant size (e.g., the lengths of trusted paths or the width of next hops are limited) are visited, the graph-simplification based trust metrics will scale well to any social network size.

5. GRAPH ANALOGY-BASED APPROACH

In this section, we review some of the major works using a graph analogy-based approach, including RN-Trust [Taherian et al. 2008], Appleseed [Ziegler and Lausen 2005], Advogato [Levien and Aiken 1998], FlowTrust [Wang and Wu 2011a], and GFTrust [Jiang et al. 2015b]. We first describe their basic ideas with examples. Next, we discuss the challenges they meet. Finally, we present the main findings of empirical studies, and we analyze their features, complexity and scalability.

5.1. Representative Models

— **RN-Trust**. Incited by the similarity between trust propagation and electric flows, in that "the less resistance there is, the more the electric current that can pass," Taherian et al. [Taherian et al. 2008] propose RN-Trust. In this work, a trusted graph is transformed into a resistive network, using the equation of $r = -logt$, where r represents the resistance and t represents the trust degree. To gain the final trust from s to d, RN-Trust first computes the equivalent resistance value, R_{sd}^{eq}. Then, the trust value can be inferred by $t_{sd} = 10^{R_{sd}^{eq}}$.
Fig. 1(c) shows an example of resistive network by using two trusted paths (s, u, d) and (s, v, d) in Fig. 2. In this example, RN-Trust will calculate resistances as follows. For edges, it has: $r_{su} = -logt_{su} = -log0.5 = 0.3$, $r_{ud} = -log0.3 \approx 0.52$, $r_{sv} = -log0.6 \approx 0.22$, $r_{vd} = -log0.7 \approx 0.15$. For each path, it has $r_{(s,u,d)} = -log0.5 - log0.3 \approx 0.82$, and $r_{(s,v,d)} = -log0.6 - log0.7 \approx 0.37$. Then, the two paths are parallel and $R_{sd}^{eq} = \frac{0.82*0.37}{0.82+0.37} \approx 0.25$. Finally, $t_{sd} = 10^{R_{sd}^{eq}} = 1.77$.

— **Appleseed**. Ziegler and Lausen [Ziegler and Lausen 2005] propose a novel local group trust evaluation method, Appleseed. In this model, an initial amount of energy $in(s)$ (indicating the trust) is injected into the source s, and then propagates into successor nodes. The more the energy a node receives, the more trustworthy he is. The authors borrow the idea from spreading activation models, and make some adaptations, as to handle more complex cases. Particularly, they use a global spreading factor δ to handle trust decay along trusted paths; they define an edge weight normalization function to make the result more reasonable, as follows:

$$e_{x \to y} = \delta * in(x) * \frac{t_{xy}}{\sum_{j \in N_x} t_{xj}}, \tag{3}$$

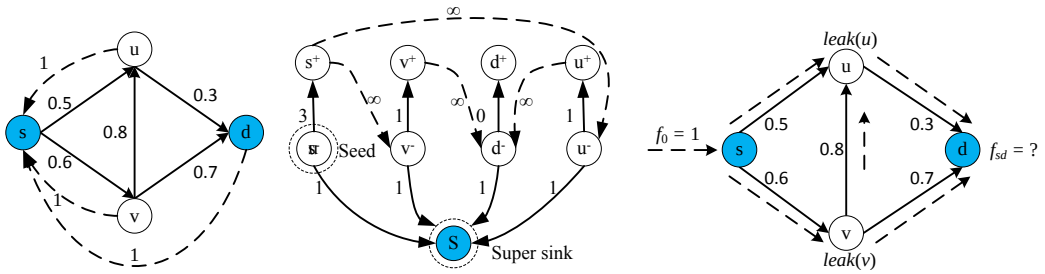
where t_{xj} is the trust degree from x to j, and N_x is the neighbor set of x. For node x, considering the total energy it receives and the decay factor, the amount of energy it can keep is calculated as follows:

$$in(x) = \sum_{x \in N_p} e_{p \to x} = \delta * \sum_{x \in N_p} (in(p) * \frac{t_{px}}{\sum_{j \in N_p} t_{pj}}) \tag{4}$$

It is worth noting that Appleseed makes use of backward propagation of trust to the source: when computing the metric, additional "virtual" edges (x, s) from every node x (Note: here $x! = s$) to the trustor s are created; moreover, $t_{xs} = 1$, indicating fully trust (see Fig. 7(a)). Next, the trust degree of x is updated as follows:

$$t_x = energy(x), or, t_x \leftarrow t_x + (1 - \delta) * in(x) \tag{5}$$

Finally, the algorithm terminates after k rounds, such that the change of trust values is not larger than some fixed accuracy threshold $T_c > 0$.
Again, we take Fig. 1(b) for instance. Suppose the initial energy $in(s) = 5$ and the decay factor $\delta = 0.85$. s will keep $energy(s) = (1 - 0.85) * 5 = 0.75$ energy, and the amount of 4.25 is distributed to its successors. Then, $e_{s \to u} = 4.25 * \frac{0.5}{0.5+0.6} \approx 1.93$, $e_{s \to v} = 4.25 * \frac{0.6}{0.5+0.6} \approx 2.32$. Since v has only one incoming edge, we have $in(v) = e_{s \to v} = 2.32$, and $energy(v) = (1-0.85)*2.32 \approx 0.35$, remaining 1.97 will be distributed to s, u and d. Similarly, $e_{v \to s} = 1.97 * \frac{1}{0.8+0.7+1} = 0.788$, $e_{v \to u} = 1.97 * \frac{0.8}{0.8+0.7+1} = 0.63$, $e_{v \to d} = 1.97 * \frac{0.7}{0.8+0.7+1} = 0.552$. Now, the energies in the two incoming edges of u are already known, we have $in(u) = e_{s \to u} + e_{v \to u} = 2.56$, and $energy(u) = (1-0.85)*2.56 \approx 0.384$, remaining 2.176 will be distributed to s and d. That is, $e_{u \to s} = 2.176 * \frac{1}{0.3+1} \approx 1.674$, $e_{u \to d} = 2.176 * \frac{0.3}{0.3+1} \approx 0.502$. Finally, we have $in(d) = e_{u \to d} + e_{v \to d} = 0.502 +$



(a) Appleseed (b) Advogato (c) GFTrust

Fig. 7. The graphs after transforming by (a) Appleseed, (b) Advogato, and (c) GFTrust.

$0.552 = 1.054$, and $energy(d) = (1 - 0.85) * 1.054 \approx 0.158$. Remaining 0.896 will be distributed to s, and we update $energy(s) = 0.75 + 0.788 + 1.674 + 0.896 = 4.108$. Up to now, a round of calculations have been done. Then, multiple rounds will be done until it reaches the termination condition. At last, whether a node is trustful or not is determined by his trust degree and a trust threshold.

Network flow theory has been used in many fields [Ahuja et al. 1993], and has been introduced into a trust evaluation system in recent years. We will mention 3 representatives of the network-flow based models: Advogato, FlowTrust, and GFTrust.

— **Advogato**. Levien and Aiken [Levien and Aiken 1998] propose the Advogato maximum flow trust metric. It identifies and cuts out "bad" nodes, as well as other nodes that certify the "bad" nodes, which are taken as the unreliable portion of the network. The computation of Advogato is conducted according to trusted "seeds." Before any computation, some nodes are taken as trusted seeds. Then, the algorithm conducts breath-first search on the graph; and assigns each node a capacity, according to the shortest distance from the node to the seed. The capacity of seed is an given input n, representing how many trustful nodes the system wants to find. The capacity of distance level $l + 1$ is calculated as: $C^{l+1} = \frac{C^l}{Average^l_{outdegree}}$, where $Average^l_{outdegree}$ is the average outdegree of trust edges $e \in E$ extending from l. In this way, nodes closer to the seed will have higher capacities, and vise versa. Moreover, nodes with the same distance level will have the same capacity. After assigning capacities, Advogato takes a transform algorithm, to convert single-source/multiple-sink graphs into single-source/single-sink. To be specific, it introduces a super sink, and it split each node x to x^- and x^+. The edge capacity is assigned to 1 from x^- to the super sink (when $C_x \geq 1$), and the remain capacity of x is assigned to edge from x^- to x^+. The capacity of edge from x^+ to y^- is set to be ∞. Finally, Advogato conducts maximum integer network flow algorithm to choose trustful nodes.
Taking the trusted graph in Fig. 1(b) for instance (neglecting the trust values on edges), Advogato will transform the graph into Fig. 7(b). The trustor s is taken as the seed, whose capacity is given as an input, here we suppose $C_s = 4$. Next, it assign capacities to 1-hop neighbors u and v. Since the out-degree of s is 2, then both neighbors get a capacity of $C_s/2 = 2$. Repeat the process and d will get a capacity of $C_d = C_u/1.5 = 1$, where the average outdegree is 1.5 for u and v. Finally, seed s will accept itself, u, v, and d as trustful peers.

— **FlowTrust**. Wang and Wu [Wang and Wu 2011a] present FlowTrust, which they consider two dimensional factors: the *trust value* and the *confidence level*. From those two factors, four metrics are deduced, namely "maximum flow of trust value," "max-

imum flow of confidence level," "minimum cost of uncertainty with maximum flow of trust value," and "minimum cost of untrust with maximum flow of confidence level." FlowTrust first computes the above four metrics using the maximum flow and minimum cost flow algorithms. Then, some algorithms are proposed to normalize the four metrics, to make the result fall into the range of $[0, 1]$. It is worth noting that the normalization may impact the final results.

— **GFTrust**. Jiang et al. [Jiang et al. 2015b] propose a trust evaluation scheme, GFTrust, using generalized flow where flow leaks as it is sent in the network. The leakage is represented as the gain factor of an edge. For instance, a flow of 3 enters into an edge (v, u), suppose the gain factor $g(v, u) = 0.8$. Then, $3 * 0.8 = 2.4$ flow will go out of the edge. [Jiang et al. 2015b] first identifies two challenges of trusted paths dependence and trust decay during propagation. Then, it addresses path dependence using network flow, and models trust decay with the leakage associated with each node. To construct a generalized network, each intermediate node x is split into x^+ and x^-; an intermediate edge (x^+, x^-) is added into the network, with the gain factor $g(x^+, x^-) = 1 - leak(x)$, and the capacity is set to be 1. The gain factor of other edges is 1. Capacities of other edges are equal to their trust values on it. The total initial flow is set to be 1, as to save the process of normalization. Finally, the calculation of trust from s to d is converted to calculate the near optimal maximum generalized flow f_{sd}. It has two steps: searching the shortest path with breadth-first search, and augmenting flow through the path. The second step contains two operations: augmenting a flow f through the selected path and calculating the residual capacity of each edge from d to s, as well as the residual flow that s can send out.
Taking the trusted graph in Fig. 1(b) for instance, GFTrust will transform the graph into Fig. 7(c). After splitting intermediate nodes and constructing generalized flow network, we let $p_1 = (s, u^+, u^-, d)$, $p_2 = (s, v^+, v^-, d)$, $p_3 = (s, v^+, v^-, u^+, u^-, d)$. Next, do the breadth-first search and find the first unused shortest trusted path, suppose it is p_2. Then, send flow from s to d through p_2. After that, record p_2 in a used path list. Suppose the leakage is 0.1 and the gain factor will be $1 - 0.1 = 0.9$. Then, the process of calculating a feasible flow is as follows: (1) Find the shortest trusted path p_2 to send flow. It results in $f_1 = 0.54$, and the residual flow of s is $1 - 0.6 = 0.4$. (2) Send the residual flow along the second shortest trusted path p_1, which results in $f_2 = 0.3$. With remaining $f(s) = 0.06$. (3) Send the residual flow along p_3. Since edge (s, v^+) remains no capacity, no more flow can be sent. (4) The final flow/trust is $f_{sd} = f_1 + f_2 = 0.84$.

5.2. Challenges: Normalization and Scalability

Normalization. Graph-analogy based models may produce a result which is out of the range of trust. Then, proper normalization will have to be done. RN-Trust uses the reverse mapping function to gain a trust value from a equivalent resistance. However, it does not mention the range of trust and how to guarantee such range. Network flow based approaches usually compute the maximum flow, and they will have to resort to normalization, as to get a reasonable result. For instance, [Wang and Wu 2011a] uses $maxT/maxP$ to normalize the maximum flow into a trust value, where $maxT$ represents the "maximum trust flow," and $maxP$ represents the "maximum number of edge-disjoint paths" from a source to a target. Advogato does not conduct any normalization, since it does not care what the exact trust value of a node is, but the rank of each node. For a general graph-analogy based model, how to design a reasonable normalization algorithm would be a big challenge. Appleseed conducts normalization for edge weight during energy diffusion. In this way, it keeps the conservation of total energy. GFTrust sets the initial flow be 1, as to guarantee the trust value fall in the range of $[0, 1]$. Hence, it avoids the normalization process.

Scalability. In general, when using a graph-analogy based model, the network scale should not be large, because of the time and space complexity. Massa et al. [Massa and Avesani 2007b] prefer the local approach for accurate evaluation of personal trust. However, if there is a need to compute all users' trust degrees, the local approach is more complex. In this case, it is more reasonable to distributively run each user's trust metric in his own machine. We believe that a better way is to combine the graph-simplification and graph-analogy based approaches: first use simplification to generate a small trusted graph; then, conduct a graph-analogy trust evaluation.

5.3. Empirical Studies and Analysis

We have conducted comparative experiments in [Jiang et al. 2015b], with respect to GFTrust, SWTrust, and some common strategies including AveR-MaxT, AveR-WAveT, MaxR-MaxT, and MaxR-WAveT. Suppose there are multiple paths from s to an incoming neighbor of d; AveR will take the average path weight as the reliability, while MaxR will take the maximum. Meanwhile, MaxT takes the direct trust of d's neighbor who has the maximum reliability, and WAveT takes the weighted average value among all direct neighbors of d. The main findings are as follows:

— The experiments verify the incentive property of GFTrust. For the pairs of s and d: (1) When GFTrust gives a higher trust $\widehat{t_{sd}}$ than the direct trust t_{sd}, there are usually several short, trusted paths between them, the length of which are $L \leq 4$. (2) On the contrary, when GFTrust gives a lower trust than the direct trust, it usually happens when there are no short, trusted paths, for which there are two sub-cases: (a) There are several long paths, which have many intermediate nodes and cause too much leakage; (b) there are not enough paths to send all the initial flow.
— The use of flow improves the metric of FScore, and the proper setting of the leakage reduces the MAE (Mean Average Error).

In the experiments, we do not compare GFTrust with other models, because it is difficult to conduct a fair comparison: RNTrust cannot deal with many scenarios; Appleseed and Advogato are group trust metrics where nodes are classified as either trustful or vicious ones; and FlowTrust has two-dimensional information of trust and confidence. Thus, we only analyze their strengths and weaknesses, as follows:

— RNTrust is elegant for its clever mapping from a trusted graph to a resistive network. However, due to the computational complexity of equivalent resistance, the network scale should not be very large. Moreover, it will be very challenging if there are overlapping paths. What may be even worse is that, it cannot guarantee that the resulting trust values fall into some specific range, e.g., [0,1].
— Appleseed and Advogato are group trust metrics, which evaluate the trustworthiness of a group of users simultaneously. Appleseed takes advantage of partial trusted graph, as to get computational scalability. Therefore, it is more efficient and can be taken as a hybrid approach of the graph-simplification and graph-analogy model. A detailed comparison of them can be found in [Ziegler and Lausen 2005].
— RNTrust, FlowTrust, and GFTrust are scalar/personal trust metrics, which calculate the trustworthiness of each user independently.
— Appleseed, Advogato, FlowTrust and GFTrust obey the rule of conservation (i.e., energy for Appleseed, flow for Advogato, FlowTrust and GFTrust).
— Similar to Appleseed, FlowTrust and GFTrust also resort to a small trusted graph. In addition, GFTrust avoids the normalization process.

Time complexity and scalability. Suppose V and E are the node set and edge set of a trusted graph, respectively. Also, suppose V' and E' are the node set and edge

set of a whole trust network/social network, respectively. Appleseed, FlowTrust and GFTrust works on a trusted graph. For RNTrust, the main work is calculating equivalent resistance in a circuit network. Using the method of mesh current analysis, the worst case complexity is $O(|V|^3)$ if it works on a trusted graph and $O(|V'|^3)$ if works on a whole network. Appleseed considers all neighbors of all nodes in a trusted graph, for which the complexity is $O(k|V||E|)$ (k is the total number of rounds after the algorithm converges). The main operations in FlowTrust and GFTrust are calculating maximum flow based on a given trusted graph, for which the complexity is $O(|V||E|^2)$ using Ford-Fulkerson method [Ford and Fulkerson 1962]. GFTrust refines the path selection process according to its specific trust evaluation task. In this way, it reduces the complexity to $O(|E|)$ in most cases. Meanwhile, in the worst cases, the complexity is $O(|V||E|^2)$. Advogato runs maximum network flow algorithm in the whole network, for which the complexity is $O(|V'||E'|^2)$ using Ford-Fulkerson method. As to the scalability, all the mentioned graph-analogy based models, except Advogato, are based on a small trusted graph, therefore, they scale well to any social network size.

6. COMMON CHALLENGES

In the above two sections, we comparatively study the graph-simplification and graph-analogy based trust models, and point out their individual challenges. Table I compares the mentioned representative models from multiple aspects of the category, the computation model, the form (discrete or continuous) and range of trust value, the information for trust, and the test data set.

In this section, we extract the common challenges that any graph-based approach may encounter, and review the existing literature. The most important four challenges are path dependence, trust decay, opinion conflict, and attack resistance.

6.1. Path Dependence

In a trusted graph, some trusted paths may be overlapping with others. For example, in Fig. 1(b), (s, u, v, d) is overlapping with (s, u, d) and (s, v, d). It is challenging to treat overlapping trusted paths, since some paths may share one or several edges. We call it the "path dependence" challenge [Jiang et al. 2015b].

Researchers (e.g., [Lin et al. 2009a; Golbeck 2005; Jøsang et al. 2006b]) have taken some action to address the challenge of path dependence. However, there is still no universally accepted solution. Existing work may ignore or reuse some information on the shared edges. For example, TidalTrust [Golbeck 2005] uses only the shortest, strongest paths, and neglect all others. [Lin et al. 2009a] uses only the shortest paths. [Jøsang et al. 2006b] takes each path (no matter wether it is overlapping with others or not) as an independent path, which reuses the information on the shared edges. Trust evidence is one of the key factors of trust evaluation. Thus, a comprehensive trust model is expected to treat trust evidence properly. Based on our experience, either evidence ignorance or reuse may lead to inaccurate results for trust evaluation. Taking Fig. 1 for instance, there are two neighbors, u and v, who express different opinions towards the trustee d. If only the shortest and strongest path is used, that is (s, v, d), the opinion of u will be neglected and may lead to an optimistic result. In contrast, if all three paths are used, i.e., (s, v, d), (s, u, d), and (s, v, u, d), the opinion of u will be considered twice; this may lead to a discouraging result.

6.2. Trust Decay

Due to the time-sensitivity of trust, it may change (usually decay) with time. Moreover, trust may decay via iterative recommendations, because people put more trust on friends than on strangers. We call the former *decay with time*, and the latter *decay with space*. The two types of decay indicates that time should be an essential factor of

Table II. Comparison of representative models on challenge-tackling.

Model*	Common Challenges				Individual Challenges		
	C1	C2	C3	C4	I1	I2	I3
TidalTrust	shortest path; information loss	yes	no	no	yes	N/A	N/A
MoleTrust	DAG, information loss	no	yes	no	no	N/A	N/A
MeTrust	$GraphReduce$; Information loss	yes	no	no	no	N/A	N/A
SWTrust	Information loss	yes	yes	yes	yes	N/A	N/A
RN-Trust	no	yes	no	no	N/A	no	no
Appleseed	partial trusted graph exploration; Information loss	yes	no	yes	N/A	yes	yes
Advogato	social network; yes	no	no	yes	N/A	no	no
FlowTrust	trusted graph; yes	no	no	no	N/A	yes	yes
GFTrust	trusted graph; yes	yes	no	yes	Yes	yes	yes

1. "C1, C2, C3, C4" represents path dependence, trust decay, opinion conflict, and attack resistance, respectively; "I1, I2, I3" represents path dependence & evidence availability, normalization and scalability, respectively.
2. Source of models: TidalTrust [Golbeck 2005]; MoleTrust [Massa et al. 2005]; MeTrust [Wang and Wu 2011a]; SWTrust [Jiang et al. 2014]; RN-Trust [Taherian et al. 2008]; Appleseed [Ziegler and Lausen 2005]; Advogato [Levien and Aiken 1998]; FlowTrust [Wang and Wu 2011a]; GFTrust [Jiang et al. 2015b].
3. In the 2nd column, the first part is the information or algorithm used to solve path dependence; "information loss" is the side effect; "yes" means solving the challenge successfully. "DAG" is short for direct acyclic graph.

a comprehensive trust model, and the length of a trusted path cannot be too long. In both cases, the pattern of decay may impact the final trust evaluation.

Some work has studied trust decay. For the decay with time, [Nguyen et al. 2012] exhibits the impact of mobility to trust decay in MANETs, and presents an analysis of the trust decay rate for some general networking and trust computation models. [Peng et al. 2013] presents a model to update trust according to some rules, e.g., "trust should increase slowly, but drop fast," and "trust should fade with time." For the decay with space, [Wang and Wu 2011b] provides parameters for user to decide decay rate. [Sun et al. 2006b] develops four axioms to serve as the principles for trust propagation, including "Concatenation propagation of trust does not increase trust" and "Multi-path propagation of trust does not reduce trust." [Jiang et al. 2015b] tries to solve path dependence and trust decay simultaneously, using a modified network flow model.

Similar to our daily life, many factors involve in the processes of trust propagation and people's opinion formulation in OSNs, including the personality of users, the time the information being created and propagated, the strength of connections, etc. Therefore, the pattern of how does the trust decay and propagation worth further study.

6.3. Opinion Conflict

Due to the subjectivity of trust, people may have different opinions towards the same target: some may give high opinions, while others give low ones. We call this phenomenon the conflict of opinions, or the controversiality of the target [Massa and Avesani 2007b]. Then, "how to combine different opinions" becomes a big challenge.

The existing work takes several ways to solve conflicts. The most common approaches include (1) taking the paths whose trust levels are above a predefined threshold, or taking the most reliable paths [Golbeck 2005], and neglecting others, which may cause

information loss; and (2) taking the weighted average or the most reliable one to gain a final opinion [Massa et al. 2005; Wang and Wu 2011a; Jiang et al. 2014; Wang and Wu 2011a; Kim and Song 2011]. Although those models can predict trust at a high accuracy in most cases, in actuality, the conflicts have not been well studied.

Currently, there is limited work particularly for conflict solving, and better solutions are expected. Research in other related fields can be introduced to solve this challenge. For instance, the research in sociology [Cialdini and Trost 1998] finds that, people often conform from a desire for security within a group. [Andersen et al. 2008] proposes several axioms for integrating trust-based recommendations from different friends, in which three opinions (positive, negative, and neutral) are considered. [Jiang et al. 2014; Jiang et al. 2015] study how a user's opinion is influenced by trusted friends, using fluid dynamics theory. Leskovec et al. [Leskovec et al. 2010a] study both positive and negative relations in OSNs. They find that a user's attitude toward another user can be estimated from their social relationships; in particular, negative relations can be predicted by exploring positive relations, and vice versa. They further study how the interplay between positive and negative relationships affects the structure of OSNs in [Leskovec et al. 2010b]. Their work may be useful for resolving conflicting opinions.

Based on several prior studies, we suggest that efforts of solving opinion conflict in trust evaluation can be made from two main aspects: one is to fully understand the personal bias and features of the trustor; the other is to deeply explore the fundamental principles regarding the formulation and evolution of people's opinions.

6.4. Attack Resistance

Trust evaluation is taken as a "soft security" mechanism compared to security schemes such as encoding. However, the trust system itself may be attacked, either by malicious or selfish users. In OSNs, users may conduct several kinds of misbehavior, such as providing bad service [Jøsang et al. 2007], sybil attack [Douceur 2002], bad mouthing [Sun et al. 2006a], on-off attack [Sun et al. 2006a], conflicting behavior attack [Sun et al. 2006a], and social spamming [Stringhini et al. 2010]. Then, "how to make a trust model resistant to possible attacks" is a more serious challenge.

A few works have been conducted for attack-resistant trust models. Levin discussed the attack resistance property of trust metrics in [Levien 2003]. He comparatively analyzes the attack resistance properties of group trust metrics and scalar ones, and he finds that the former is better. Sun et al. [Sun et al. 2006b] discuss several attacks of trust models. Jiang et al. [Jiang et al. 2014] study two types of collusion and non-collusion attacks. [Jiang et al. 2015b] proposes a flow-based model which provides social incentive compatibility and sybil tolerance. Hoffman et al. [Hoffman et al. 2009] study attacks in reputation systems, where they identify possible components that are vulnerable to attacks and compare several defense mechanisms.

Although much work has been done, due to the open and dynamic nature of OSNs, and the variety of online attacks, there is a lack of comprehensive work that can handle all possible attacks. Therefore, a combination of trust and security models may be expected. An attack-resistant trust model should be able to punish malicious behaviors and provide more incentive techniques to encourage user cooperation.

Table II shows a summary of representative models from the aspects of their challenge handling effects. We can see that, it desires more attention to design comprehensive trust models that can handle more (or even all) possible challenges.

7. PRE-AND-POST PROCESSES

In the above sections, we review and discuss trust evaluation regarding the evaluation process. In this section, we will take a look at the work which needs to be done before and after the model, that is, the preparation (i.e., collecting information for trust and

constructing trusted graph), the validation of the performance, and the applications in which a trust model can be incorporated (see Fig. 6)

7.1. Preparation

Information Collection for Trust. As we have mentioned before, trust is commonly taken as being subjective and personal; trust can also be specific or general. Information collected for forming a trust can be either one-dimensional or multi-dimensional [Gefen 2002; Wang and Wu 2011a; Yao et al. 2013]. Trust can be represented by a scalar number. It can be continuous and normalized to the range [0, 1]; it can also be binary (0 or 1 in Epinions) or discrete levels (e.g., [1, 5] in Amazon). In [Theodorakopoulos and Baras 2006], trust is measured by a tuple of rating values and confidence values from [0,1]; A total trust corresponds to the highest rating (which is 1) and full confidence (again 1). Li and Wu [Li and Wu 2010] give a more general confidence measure that depends on both frequency and duration of a contact. Jøsang et al. [Jøsang 1999] use subjective logic, and propose to use a triplet to represent a trust: belief (b), disbelief (d), and uncertainty (u), normalized such that $b + d + u = 1$.

TidalTrust [Golbeck 2005] takes user ratings as the information used for predicting trust. MoleTrust [Massa et al. 2005] uses the web of trust to indicate whether to trust or not. SWTrust [Jiang et al. 2014] uses $domain$ for inferring trust, which is objective and stable. MeTrust [Wang and Wu 2011a] takes multiple dimensional information into consideration. [Gefen 2002] propose a three-dimensional trust metric for e-commerce environments, in which the trust is consist of "trustworthiness dealing with integrity", "benevolence", and "ability in the unique case of online consumer trust." RN-Trust [Taherian et al. 2008] assumes that trust information is already known. Advogato [Levien and Aiken 1998] decides the capacities of nodes according to their distance with seeds. FlowTrust [Wang and Wu 2011a] considers the confidence level and the trust value. However, how to get the information is not mentioned.

Some other information is being incorporated into a trust evaluation system. Jiang et al. [Jiang et al. 2013; Jiang et al. 2015a] present the idea to evaluate trust by selecting proper recommenders, in which they identify four metrics to estimate the quality of recommenders, namely the "trustworthiness," "influence," "uncertainty," and "cost." Gefen et al. [Gefen and Pavlou 2012] study the boundaries of trust and risk. Liu et al. [Liu et al. 2013b] propose the MFPB-HOSTP algorithm, as to select optimal trusted paths with multiple constrains. They consider three metrics of "trust," "social intimacy degree," and "role impact factor." Yao et al. [Yao et al. 2013] propose MATRI, in which they take "multiple aspects," "transitive trust," and the "bias" into consideration. Table I summarizes the information used for trust.

Trusted Graph Construction. As we have mentioned before, there is a need to generate a small trusted graph. SWTrust [Jiang et al. 2014] is proposed exactly for this aim. It takes advantage of weak ties, by differentiating local neighbors from long contacts. Then it prefers long contacts to construct trusted chains, so as to improve the coverage and reduce the cost. Yao et al. [Yao et al. 2012b] also target the issue and proposed a two-stage method. One stage is path selection, the other stage is component induction. Zuo et al. [Zuo et al. 2009] propose a framework for trust evaluation using a set of trusted chains. They also provide a notion of a "base trusted chain set." However, no algorithm is developed to identify the set.

7.2. Model Evaluation

Evaluation Method. There are two typical ways to evaluate the performance: (1) using the feedback by simulation (due to the lack of enough real feedback), such as in [Caverleea et al. 2010]; and (2) using the leave-one-out method, such as [Massa and Avesani 2007a; Jiang et al. 2014]. Fig. 8 shows the illustration of the method:

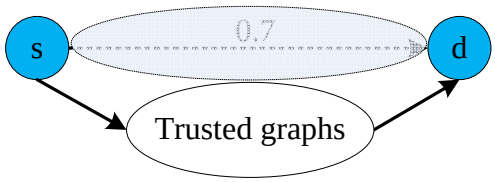


Fig. 8. The illustration of the leave-one-out method.

mask the direct edge (s, d), and calculate trust via a trusted graph; the performance can be evaluated by comparing the masked and calculated values, to check how close the two values are. For instance, suppose we have a data set which has 100 pairs of trust relations (i.e., direct edges). For each pair (edge), the original edge (say, (s, d)) and trust value will be masked (i.e. assuming there is no such edge), and a trusted graph will be constructed by searching for proper trust chains from s to d. Based on the trusted graph, an algorithm can be implemented and a calculated trust value can be gained and recorded. After that, edge (s, d) will be recovered, and the next edge will be treated in the same way. After all 100 pairs have been considered, we can measure the performance by calculating accuracy metrics (e.g., Precision, Recall, FScore). It is worth noting that not all test pairs have trust chains (other than direct relation) between them. Therefore, the *coverage* representing the ratio of predictable test pairs over the total number of test pairs is also an important metric.

Evaluation Metrics. Two most commonly used metrics are the *coverage* and *accuracy* of trust prediction. The former represents the ability of the algorithms to provide a prediction, i.e., the percentage of trust relationships that are predictable (at least one trusted path is available between two users). Meanwhile, the latter represents "the ability of predicting whether a user will be trusted or not [Jiang et al. 2014]."

— *Coverage*. Let Γ be the amount of source/target pairs that are predictable, and $Total$ be the total number of test pairs. Then, $Coverage = \Gamma/Total$. The following metrics are defined for prediction accuracy.
— *MAE* (Mean Absolute Error). It is calculated as $MAE = \sum(t_{sd} - \hat{t_{sd}})/\Gamma$, where t_{sd} and $\hat{t_{sd}}$ denote the real and predicted trust values, respectively.
— *(RMSE)* (Root Mean Squared Error) [2]. The metric of RMSE is deemed as an improvement of MAE [Massa and Avesani 2006]. It is calculated as $RMSE = \sqrt{\sum(t_{sd} - \hat{t_{sd}})^2/\Gamma}$.
The metrics of MAE and RMSE represent how close the predictions are to the real trust values; a smaller MAE or RMSE indicates a higher prediction accuracy.
— *Precision*. It represents the fraction of users who are predicted to be trusted, and are really trusted ones. It can be calculated as $A_t \cap B_t/B_t$, where A_t is the number of source/target pairs in which the source trusts the target directly, and B_t is the number of that in which the source trusts the target by the calculated trust.
— *Recall*. It is the fraction of users who are really trusted, and are successfully predicted. It is calculated as $A_t \cap B_t/A_t$.
A higher Precision and Recall indicates a higher prediction accuracy.
— *FScore*. It is calculated as 2·Recall·Precision/(Recall+Precision).
The equation implies the purpose of FScore metric: to combine the metrics of Recall and Precision, and to provide a joint measure.

[2] http://en.wikipedia.org/wiki/Root-mean-square_deviation

Data Set. All online social networks (e.g., Facebook, Myspace, etc.) are potential testbeds for trust models in OSNs. However, most of them may not have explicit trust information. Here, we introduce three commonly-used real social network data sets with explicit trust: Advogato (www.advogato.org), Epinions.com (www.epinions.com), and FilmTrust (http://trust.mindswap.org/FilmTrust).

The web site of Advogato is designed by Levin [Levien and Aiken 1998] for free software development, and for testing the Advogato algorithm. Since then, it has been widely used in testing other trust models. On Advogato, users can rank others with four choices: Observer, Apprentice, Journeyer, and Master, which can be assigned 0.4, 0.6, 0.8, and 1.0, respectively, to numerate the level of trust. The snapshots can be found at [tru 2014a; tru 2014b].

Epinions is a good testbed that is widely used in the research of trust evaluation and trust-based recommendation [Massa and Avesani 2007a], because it has both the information of user trust relationships and user-item ratings[3]. Users can review items and assign them numeric ratings in the range of [1, 5]. They can also build their own trust network by adding the people whose reviews they think are valuable. One data set of Epinions.com is published by Massa [Massa and Avesani 2006; tru 2014c]. Tang et al. [Tan 2014; Tang et al. 2012] publish a data set of Epinions with more information including time stamps. The data set of a very similar web site, Ciao, is also provided in [Tan 2014]. [Richardson et al. 2003; SNA 2014] also provide data set of Epinions.

FilmTrust is developed by Golbeck [Golbeck 2005] for the testing and validation of trust models. It is a website on which users are encouraged to write reviews and provide ratings on movies or others' reviews. Each user in the website can derive personalized movie ratings, based on his friends' ratings. Trust is also used to sort reviews.

7.3. Applications

Trust evaluation has many applications. Just mention a few: in the survey of [Grandison and Sloman 2000], the authors describe some influential examples of trust management, including information retrieval systems, medical information systems and mobile code. In [Jøsang et al. 2007], the authors introduce several real applications, including discussion fora (e.g., Slashdot), product review sites (e.g., Epinions) and expert sites (e.g., AllExperts [All 2014], Advogato [Levien 2003]). In this article, we mainly introduce two of the most popular trust-based applications: trust-based/trust-incorporated security management and trust-based recommendation.

— **Trust-based/trust-incorporated security management**. Trust management is developed as an answer to the inadequacy of traditional authorization mechanisms [Blaze et al. 1999]. It can be taken as a "soft security" mechanism. It uses collaborative methods to assess members' behaviors, identify those who behave well or not well, and provide corresponding measures [Jøsang et al. 2007]. The examples include the famous e-commerce websites (Taobao[4] in China, Amazon[5] in the US, etc.). Pretty Good Privacy (PGP) is the first system which use the term "Web of Trust." It is a program for data encryption and decryption, and it can enhance the security of data communication [Heinrich 2011]. Several important works have been proposed to detect and defence sybil attack, i.e., SybilGuard [Yu et al. 2006], SybilLimit [Yu et al. 2008], SybilInfer [Danezis and Mittal 2009], SumUp [Tran et al. 2009], and so on.

[3]Unfortunately, eBay has discontinued allowing users to write reviews or rate other reviews, beginning in March 2014.

[4]http://www.taobao.com/

[5]http://www.amazon.com/

In addition, Wang et al. [Wang et al. 2013] propose a trust-based framework (called ARTSense) and apply it in participatory sensing networks.

— **Trust-based recommendation**. One important application of trust is in a recommendation system, where users take advice from friends. A recommendation system is based on trust propagation [Amatriain 2012; Machanavajjhala et al. 2011; Yang et al. 2011a; Yang et al. 2011b] and is widely used in OSNs. Such a system includes two essential components: the *rating* (or opinion) of a user on an item and the *influence* of a user on another user when he recommends an item [Zhu et al. 2012; Yang et al. 2012; Bakshy et al. 2012]. Here, an item can represent different things according to the context, including a user, a view, a real commercial product, etc. Systems that support rating, ranking, and reputation include Amazon and eBay's recommendation systems [Houser and Wooders 2006], and Epinions' web of trust [Tan 2014].
Trust-based recommendation systems aim to produce recommendations for individuals, based on the opinions of trusted friends. This approach can help to solve the sparsity issue in other approaches and provide more suitable recommendations. The challenge of designing an appropriate trust-based recommendation model is that of efficiently capturing time-evolving ratings and influences from users to items and from users to users, respectively. That is, we need to show how recommendations are propagated through influences among trusted users, which are highly personalized.
Almost all the trust-based recommendation systems are working with a trusted graph. We briefly review some representative works in this area, again following the two categories of graph-simplification and graph-analogy based approaches.
  — *Graph-simplification based Recommendation*. Massa et al. [Massa and Avesani 2007a] study the recommendation system and propose to use trust relations for improve the quality of recommendation. They conduct experiments on Epinions data set, and the results show the advantage of over the traditional collaborative filtering (CF) approach, especially for cold-start items and users. In addition, Andersen et al. [Andersen et al. 2008] explore several axioms for trust-based recommendation. They discuss some typical recommendation systems and analyze which set of axioms are suitable for each system.
  — *Graph-analogy based Recommendation*. Jiang et al. [Jiang et al. 2014; Jiang et al. 2015] propose a time-evolving rating prediction scheme in trust-based recommendation systems, using fluid dynamic theory. A user is modeled as a container; the trust-based recommendation is modeled as fluid; and the trust relations serve as the pipe connecting containers. Several social and physical principles are proposed or examined in FluidRating, such as "first influence dominates," "stronger influence dominates," "Mass conservation" and "energy conservation". A similar approach is used in influence diffusion. For instance, [Ma et al. 2008; Yang et al. 2007] use another physical phenomenon called heat diffusion. As heat always flows from a position with high temperature to a position with low temperature, seeding users are given a high amount of heat that will be diffused to other users.

— **Trust visualization**. Another method of trust dissemination is trust visulization. Generally, this application evolves an overview analysis of the network status in terms of trust. The result can be reported to social service providers. However, it is beyond the scope of this paper, since our focus is on personalized trust evaluation.

8. CONCLUSION AND OPEN CHALLENGES

To the best of our knowledge, our paper provides the first review that focuses on the graph-based trust evaluation in OSNs. We follow the two categories of "graph-simplification" based and "graph-analogy" based approaches, and we discuss their individual problems and challenges. Then, we discuss the common challenges of all graph-based models. We also conduct a brief review of the preparation and the validation

of trust models, including information collection, performance evaluation, and trust-based applications. Finally, we would like to mention more open challenges for further research, which are not restricted to graph-based approaches, but may be encountered by any trust model. They are the privacy issue, the standard test bed, and the distrust.

Privacy Preservation. The information used by existing trust models is explicitly expressed, or at least is assumed to be. In fact, it is not easy to get the trust information, since there are fewer people who give trust opinions than those who evolve in online interactions. Or, if it (trust information) can be gained, the privacy issue emerges. Currently, the privacy preserving schemes usually take advantage of some encoding techniques. For example, [Wang et al. 2013] proposes ARTSense, as to solve the problem of "trust without identity" in participatory sensing networks, in which they use the blind signature technique to protect user privacy. How to reach the balance between trust evidence collection and privacy preservation is very challenging.

Feedback and Test Bed. To test the performance of different trust models, we need feedback from users and standard test beds. However, due to the concern of privacy and the fear of retorsion, there is less feedback than interactions. As far as we know, there is no commonly-accepted evaluation benchmark, that would allow for a comparison of the trust models in OSNs under a set of representative and common conditions. Hence, how to collect feedbacks and develop test beds is very meaningful but challenging.

Distrust. While no trust means we have no idea about someone's trustworthiness, distrust indicates doubt about someone's trustworthiness. Some work (e.g., [Guha et al. 2004; Ziegler and Lausen 2005]) has considered to cooperate distrust into trust models. Meanwhile, some others prefer to deal with them separately. The reason is that, distrust may not be propagative. Taking Fig. 1(b) for instance, if s distrusts u, and u distrusts v, it is not likely that s will distrust v. The intuition behind this is "The enemy's enemy is my friend [Antal et al. 2006]." In OSNs, distrust has to be carefully designed to avoid retaliatory negative feedback. From this point of view, dealing with distrust is even more challenging than dealing with trust. [Tang et al. 2015] investigates negative link prediction problem with only positive links and content-centric interactions in social media. It indicates that researches on distrust can be closely related with trust. Therefore, although closely related in concepts and applications, the rules of evaluating distrust may be related, but different from that of trust.

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